Comparison of multilayer perceptron and nonlinear autoregressive models for wind speed prediction

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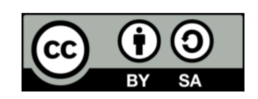
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ABSTRACT

Wind energy is a critical component of the global shift to renewable energy sources, with significant growth driven by the need to reduce carbon emissions. Accurate wind speed prediction is crucial for increasing wind energy output since it directly influences wind farm design and performance. The purpose of this study is to compare two artificial neural network (ANN) models for predicting wind speed in Dakhla City, a place with a high wind energy potential. The first model is a multilayer perceptron (MLP) trained with the backpropagation algorithm, while the second is a nonlinear autoregressive with exogenous inputs (NARX) model, a form of recurrent neural network (RNN) noted for its ability to handle time-series data more well. The comparative analysis results show that the NARX model outperforms the MLP model in terms of wind speed forecast accuracy. The NARX model achieved a near-perfect regression coefficient (R) of 0.9998 and a root mean square error (RMSE) of 1.02899, indicating that it can represent complex, nonlinear wind speed patterns. These findings indicate that the NARX model could be a beneficial tool for increasing the efficiency of Dakhla City's wind energy infrastructure, assisting the region in meeting its renewable energy ambitions.



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1. INTRODUCTION

The worldwide demand for energy has surged significantly, driven by rapid industrial expansion in developed nations and increased business investments in countries with lower production costs [1]. This surge in demand has led to a corresponding increase in the price of crude oil, the primary source of energy. However, the world's oil supply is rapidly depleting, indicating a future shortfall in meeting energy needs [2]. The reliance on conventional energy resources is becoming unsustainable due to environmental concerns and the finite nature of these resources. As a result, the shift towards renewable energy resources is not only inevitable but also essential for the sustainable progress of humanity [3].

Wind energy, in particular, has emerged as a leading renewable energy source due to its abundance, sustainability, and potential for large-scale energy production. Unlike fossil fuels, wind energy is clean and does not produce greenhouse gases, making it environmentally friendly. Wind farms can be established onshore and offshore, taking advantage of areas with high wind potential. The global capacity for wind energy has been growing steadily, supported by technological advancements in wind turbine design and increased investment in renewable energy infrastructure. Efficient wind energy utilization can significantly contribute to reducing

dependence on fossil fuels, enhancing energy security, and mitigating climate change impacts. Forecasting wind speed is crucial for efficiently managing wind power generation systems [4]. Accurate wind speed predictions provide vital information for developing effective strategies to optimize energy production, stabilize the electricity supply, and reduce the gap between electricity demand and supply [5]. To achieve optimal electrical energy production, several meteorological, mechanical, and electrical characteristics must be considered. Wind, typically defined by its speed and direction, significantly influences energy production [6]. Other factors such as temperature, humidity, pressure, and dew point temperature also play a role, despite their unpredictable and random nature. Various methods exist for forecasting these conditions [7].

Historically, wind speed forecasting has relied on traditional statistical methods such as auto-regressive moving average (ARMA) and auto-regressive integrated moving average (ARIMA) models, which are effective for time series data but often struggle with the nonlinearity of wind data [8]. Auto-regressive with exogenous inputs (ARX) models, while linear, are commonly used but also face limitations in capturing the complex dynamics of wind patterns. As wind data is inherently nonlinear and complex, more advanced techniques are required. Recent advancements in artificial intelligence (AI) have introduced methods such as artificial neural networks (ANN), support vector machines (SVM), and hybrid models like adaptive neuro-fuzzy inference system (ANFIS), which have shown promise in enhancing the accuracy of wind speed predictions by effectively modeling nonlinear relationships [9].

Our study focuses on short-term wind speed forecasting in Dakhla City, utilizing three years of meteorological data (2018, 2019, and 2020) recorded at hourly intervals. Accurate short-term forecasts are essential for operational planning and management of wind power generation [10]. Multiple strategies exist for tackling the challenge of wind forecasting, with statistical methods being particularly prominent [11]. These methods are subdivided into several categories, with time series analysis being a key approach. The most well-known examples are ARMA models [8]. Box and Jenkins introduced ARIMA as a predominant model for wind energy forecasting. ARIMA models are widely utilized due to their effectiveness in handling time series data. Additionally, ARX models, which are consistently linear, are extensively used. However, the nonlinear nature of wind requires more sophisticated approaches. In recent years, AI methods such as ANN, SVM, and hybrid models like ANFIS have been employed to address the nonlinear and complex nature of wind speed data [9], [12] to address nonlinear and complex models.

These methods have shown promise in improving the accuracy of wind speed predictions. Our study aims to forecast wind speed in Dakhla City using three years of meteorological data (2018, 2019, and 2020) recorded at hourly intervals. We use supervised learning to solve our regression problem, with two different types of neural networks. The first is the multilayer perceptron (MLP) neural network, which has numerous layers and transmits information from the input layer to the output layer via a feedforward propagation network. The second is the recurrent neural network (RNN) processed by the nonlinear autoregressive with exogenous inputs (NARX) model, which includes loops that allow the storage of information within the network [13]. These loops enable the network to maintain a memory of past inputs, making it well-suited for time series forecasting. By comparing the performance of MLP and NARX models, our study aims to identify the most effective approach for wind speed forecasting in Dakhla City. This research contributes to the broader field of renewable energy by providing insights into the application of advanced neural network models for improving wind speed prediction accuracy.

2. METHOD

The goal of this study is to discover which predictive network, MLP or NARX, is best effective at forecasting wind speed in Dakhla. Dakhla is located in southern Morocco and covers 130,898 km², with coordinates of 23° north latitude and 15° west longitude. The city is notable for its continuously windy climate, with winds gusting up to 30 km/h year-round. Weather data for Dakhla was gathered hourly for three years, from 2018 to 2020. This information is available on the website (info climate [14]).

Table 1 shows the hourly data in local time, which includes wind speed, temperature, atmospheric pressure, dew point temperature, and humidity. The table also emphasizes the advantages of preprocessing in improving the consumption and extraction of meteorological data. We processed the meteorological data in Excel before doing MLP modeling with NNTOOL and NARX modeling with NNSTART in MATLAB [15]. Preprocessing weather data makes it easier to select parameters for predictive models. To reduce computational expenses, it is recommended to limit the number of variables in the model input.

Table 1. Introducing the Dakhla weather data sheet

Date	Hours	Temperature (°C)	Wind speed (km/h)	Pressure (hpa)	Humidity (%)	Dew point temperature (°C)
01/01/2018	00	21.6	11	1030.3	31	3.8
01/01/2018	23	22	11	1029.5	40	7.7
01/01/2018	22	21.8	7	1029.1	40	7.6
01/01/2018	21	18	37	1022	37	14
01/01/2018	20	20.8	11	1028.6	46	8.8
01/01/2018	19	19.3	7	1028.2	58	10.9
01/01/2018	18	20.7	4	1027.8	57	11.9
01/01/2018	17	22.3	4	1027	53	12.2

2.1. Artificial neural networks

The genesis of the ANN, an information processing model, drew its inspiration from the intricate workings of the human brain [16]. Learning algorithms based on statistical methods are used to improve these networks. They are located on the one hand in the category of statistical applications, which allows them to create extensive, flexible and partially structured functional spaces, and on the other hand in the sphere of artificial intelligence techniques, promoting decision-making which rely more on perception than on formal logical reasoning.

Therefore the formal neuron is an abstract representation of biological reality. It mathematically expresses all the observable information of a real neuron, with the exception of the temporal criterion, which does not need to be included in the model, because the values manipulated by the neurons represent the emission frequencies of the stimuli [17].

A neural network is typically composed of several key components. It is characterized by inputs $(x_0, .., x_n)$ that come from previous neurons, with each input associated with a weight (w) representing the connection strength. These weight values are calculated during the learning phase in the hidden layer, which consists of several neurons and an activation function $a = \sum(w_{nj} \cdot x_n)$. Here, xn represents the inputs of the network, and w_{ij} represents the weights associated with each neuron. The activation function can take various forms, with the most commonly used being the linear function, hyperbolic tangent, and sigmoid function. The output layer is generally characterized by a linear function, [11], [15]. The formal neuron is presented in Figure 1 [18].

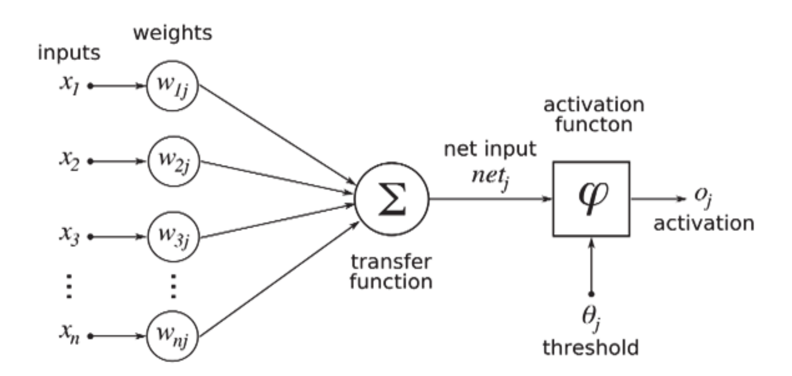


Figure 1. Formal neuron presentation

As previously noted, we used two types of neural networks. The MLP [19] is a standard neural network that consists of input, hidden, and output layers. It uses the error backpropagation algorithm, which is essentially based on gradient descent. This backpropagation algorithm calculates the difference between the desired output and the outputs produced by the network. To mitigate this mistake, information is passed from the output to the input by modifying the weights [20]. Other traditional neural networks in the backpropagation family are adaptive linear neuron (Adaline), multi-Adaline (Madaline), and radial basis function (RBF), which is architecturally similar to the perceptron MLP.

Unlike formal neurons, which are limited to input and output layers, a MLP is a neural network model that integrates hidden layers to perform intermediate processing aimed at improving predictions [21]. Neural outputs are activated through the use of nonlinear functions, such as the tangent-hyperbolic function or the logistic function. It is possible to train a network with multiple hidden layers and neurons using these models. In this way, the more layers there are, the larger the network and the richer the model becomes. We talk about deep learning [22]. Figure 2 [23] is an example of a MLP that has a hidden and output layer.

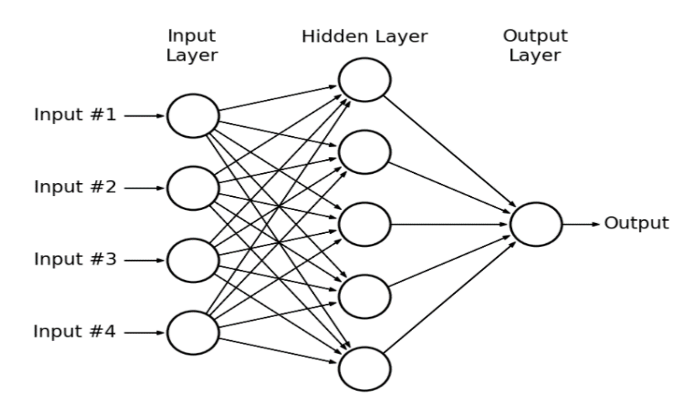


Figure 2. Example of MLP

NARX, a variation of recurrent neural networks, employs training methods akin to those found in traditional networks using the gradient back propagation algorithm [24]. NARX distinguishes itself by its capacity to effectively analyze nonlinear time series, particularly dynamic systems. Additionally, its gradient descent algorithm demonstrates swift convergence in comparison to alternative networks. Various other forms of deep recurrent neural networks exist as well [25]. An illustration of the NARX-NN structure, featuring both a closed loop and an open loop, can be observed in Figures 3(a) and (b) [26], [27].

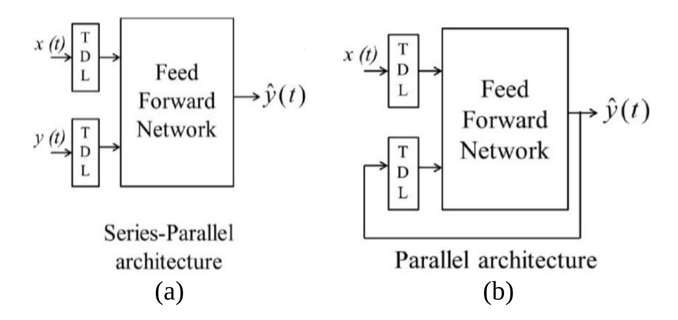


Figure 3. Example of NARX architecture; (a) open loop arrangement and (b) closed loop arrangement

Some case studies have used the NARX model to analyze hourly solar radiation prediction. Additionally, other studies have applied the NARX model for forecasting wind speed. The researchers [27] did a study on predicting daily direct sun radiation using the NARX model and discovered that it produced strong results throughout periodic training. Similarly, Hamdan *et al.* [28] projected hourly sun radiation in Amman using three different neural networks: NARX, Feedforward, and Elman. In their investigation, the NARX model beat the others, achieving the greatest results in both the training and validation phases of solar data prediction.

To assess solar radiation in [29] created seven alternative NARX network models by altering input parameters, the number of neurons, and the number of time delays. The results showed that the model with three factors (temperature, humidity, and wind speed) was the most effective at estimating solar radiation.

Mohammed *et al.* [30] also applied the NARX model to forecast hourly solar radiation in Amman. To assess the NARX model’s performance, they kept the same model structure while changing the training algorithms: Levenberg-Marquardt (LM), resilient backpropagation (RP), scaled conjugate gradient (SCG), conjugate gradient with Polak-Ribiére updates (CGP), conjugate gradient with Fletcher-Reeves updates (CGF), conjugate gradient with Powell-Beale restarts (CGB), and one-step secant backpropagation (OSS). They determined that the LM algorithm was the most successful. Other types of networks, such as convolutional neural networks (CNN), can also predict wind speed. In addition, there are numerous learning algorithms such as SVR, SVM [31], fuzzy logic [32], ANFIS [33], and genetic algorithms [34].

3. RESULTS AND DISCUSSION

Meteorological data was handled using NNTOOL to facilitate modeling. To optimize the input variables for our neural network and avoid the computational cost of using all of the variables listed below, we calculated their correlation coefficients. Table 2 shows a strong relationship between temperature and dew

point temperature, with the highest correlation coefficient of 0.4997. This implies that the dew point temperature is comparable to the temperature and will have no significant impact on training. As a result, we decided to abolish the dew point temperature variable.

Table 2. Correlation coefficients between variables

	Temperature	Wind speed	Pressure	Humidity	Dew point temperature
Temperature (°C)	1	-0.0238	-0.3081	-0.2928	0.4997
Wind speed (km/h)		1	-0.2040	-0.1866	0.0270
Pressure (hpa)			1	-0.1652	-0.5022
Humidity (%)				1	0.4817
Dew point temperature (°C)					1

After several attempts, we varied the number of inputs, starting with three: wind speed at (t-1), pressure at (t-1), and temperature at (t-1), and then added a fourth: humidity at (t-1). We also experimented with different numbers of neurons in the hidden layer, ranging from 5 to 25, to determine the ideal configuration for accurate wind speed prediction. Our research revealed that the network with four inputs (wind speed, pressure, temperature, and humidity at (t-1)) and 25 neurons in the hidden layer was the most effective. This design routinely outperformed other configurations in terms of prediction accuracy and processing efficiency. We used mean square error (MSE) and root mean square error (RMSE) to compute the difference between the desired and computed outcomes. These measures are used to assess the effectiveness of prediction models, with lower values indicating higher accuracy.

To find the optimum neural network design, we computed the MSE and RMSE for each of the scenarios listed above.These errors quantify the discrepancy between the desired and computed outputs and are expressed by (1) and (2) [35].

$$MSE = \frac{1}{n}\sum_{n}^{1}(O - d)^2 \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{n}^{1}(O - d)^2} \quad (2)$$

with O is calculated output and d is desired output.

3.1. Multilayer perceptron

The MLP network's training process is depicted in the Figure 4. The model initially undergoes adjustments through training, which enables it to become familiar with and comprehend the data. Subsequently, during parameter configuration, validation is employed to evaluate the model's fitness. Creating an efficient model requires adjusting the parameters (weight and bias). Ultimately, the testing phase serves as the final evaluation to refine and organize the model [36]. MLP with backpropagation using the LM algorithm can be observed in Figure 4.

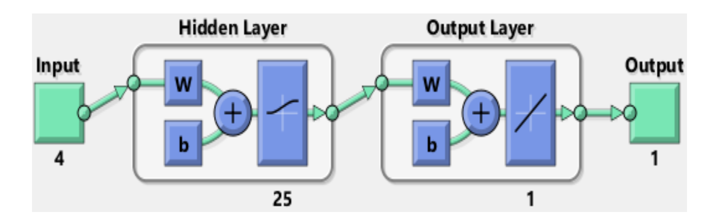


Figure 4. MLP with backpropagation using the LM algorithm

Figure 5 depicts the processes for training the MLP network. First, data is used to fit the model, which implies the model must observe, process, and learn the data. Second, validation is performed to evaluate the model fit while defining the parameters. The goal is to optimize the parameters (weights and biases) to produce a strong model. Finally, the testing process performs the final examination of the model to make it more organized. However, as illustrated in Figure 5, the R values for the training, validation, and test phases were 0.51837, 0.5113, and 0.50597, respectively, which are all relatively low. This indicates the model's inability to generate accurate predictions and produce appropriate results. Overall, we determined that the LM backpropagation strategy produced mediocre results, with an R-value of 0.51539.

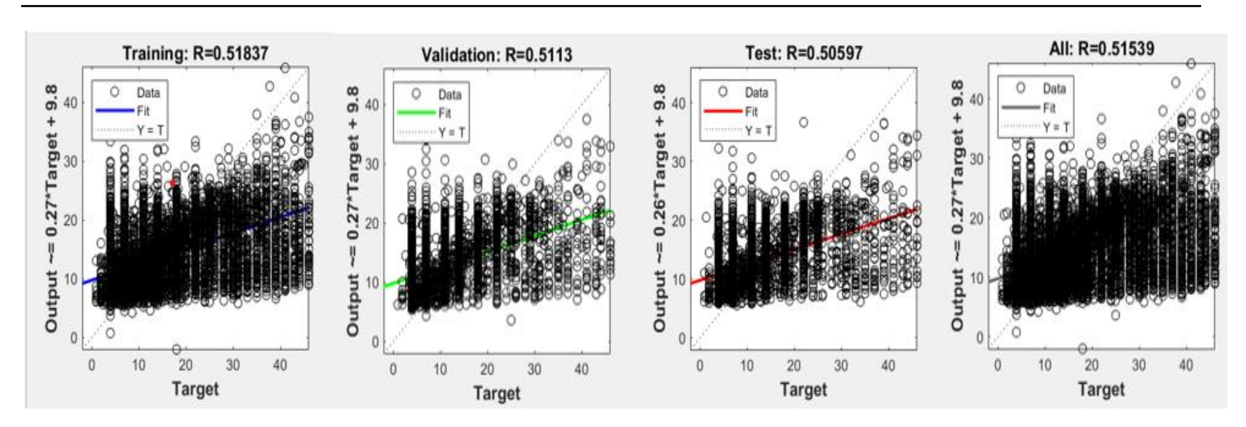


Figure 5. The regression rate is demonstrated using LM back propagation

After training the MLP using LM backpropagation, we concluded that the model was not able to properly train and clearly predict the proposed inputs. Figure 6 shows the mismatch between the actual series and the predicted series. We conclude that the MLP is too classical a model and is still not able to solve high complexity problems. It vividly illustrates the significant contrast between the model predicted wind speed and the observed wind speed. The disparity between these two datasets is undeniably clear.

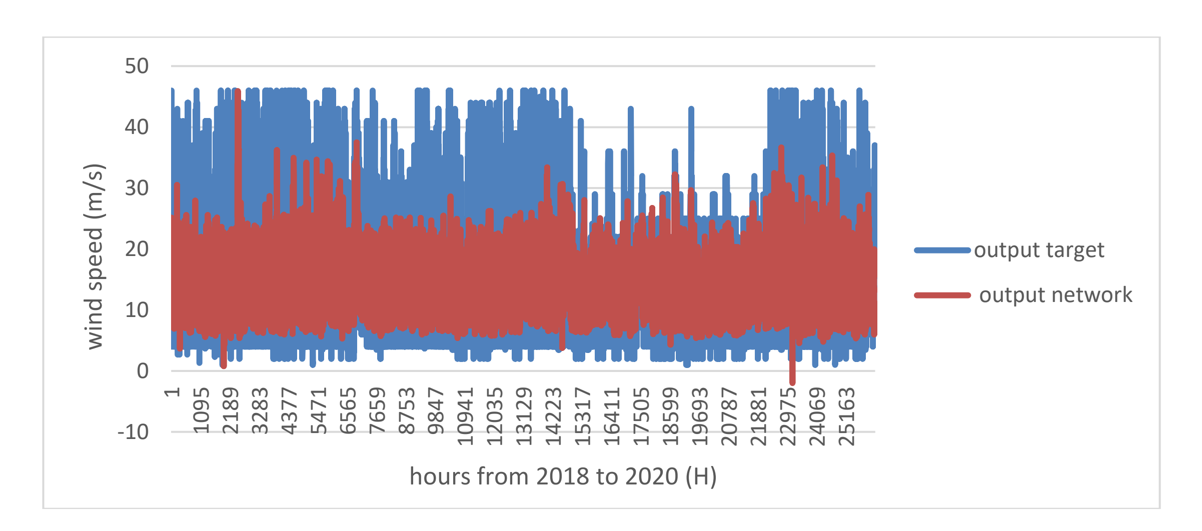


Figure 6. Using the LM back-propagation model to predict wind speed

3.2. Nonlinear autoregressive with exogenous input open loop

The NARX model's input layer has four external inputs; the hidden layer contains twenty-five neurons that implement a hyperbolic tangent function with two time delays; and the output layer includes an endogenous input guided by a linear function. Our NARX-SP model was trained with the SCG backpropagation algorithm, the results are very satisfactory and very significant than the first model which is the MLP trained by LM backpropagation. The learning phases are always 3, of which we took the same sampling distribution, 80% of the database for the training phase, 10% for the validation phase and 10% for the test phase. All the phases demonstrated that the model is able to predict the wind speed 24 hours ahead. The Figure 7 shows the NARX model using SCG method.

Figure 8 shows the results of the NARX model, which was optimized with the SCG algorithm. The training, validation, and testing phases have coefficients of determination (R values) of 0.99998, 0.99998, and 0.99995, respectively. These high R values suggest a virtually perfect fit of the model to the data at all stages, demonstrating the model's robustness and accuracy. When comparing the NARX model's performance to that of the LM model, it is obvious that the NARX model's predictions are quite similar to the actual wind speed data. This is corroborated by a high correlation coefficient (R=0.9998) between expected and actual wind speeds, demonstrating a strong linear relationship with low forecast error.

Figure 7. NARX model using SCG method

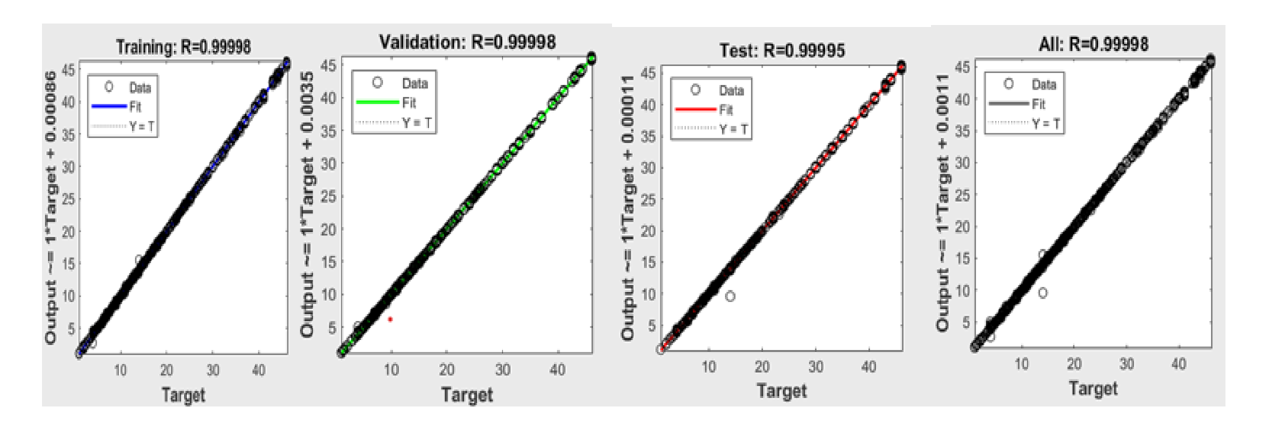


Figure 8. Presentation of regression rates for SCG

Figure 9 shows the results of the NARX model, which was processed using SCGs. The R values for the training, validation and testing periods are 0.99998, 0.99998, and 0.99995, respectively. Examining the LM model, the NARX data closely align with the actual wind speed data, exhibiting a correlation coefficient of R=0.9845. Figure 9 shows a visualization of both anticipated and real wind speeds, demonstrating the NARX model's outstanding performance in wind speed prediction.

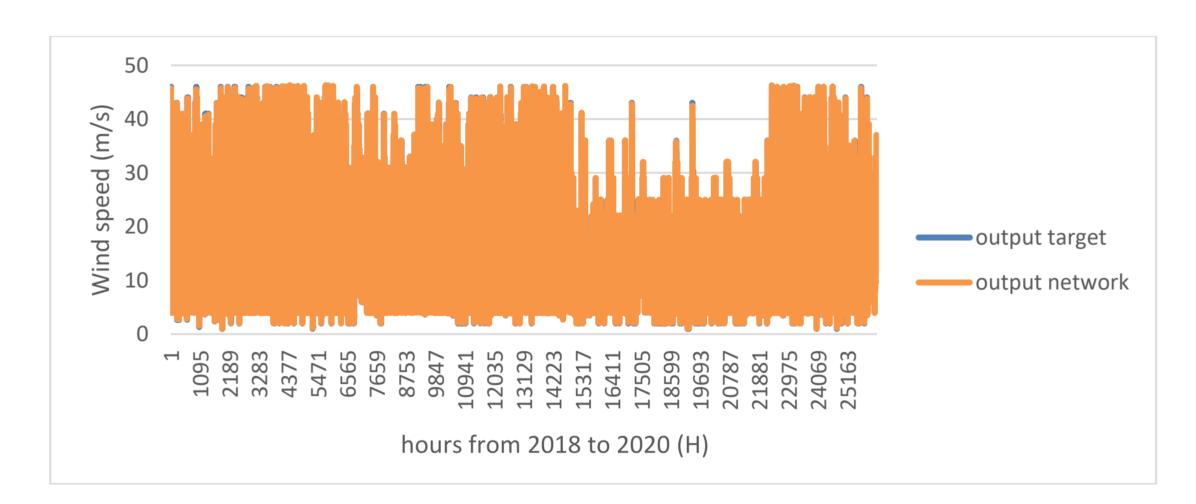


Figure 9. Graph depicting the prediction of wind speed utilizing the NARX model

In Table 3, we used RMSE, a metric widely used in climatology, forecasting, and regression research. The choice was made to validate the data and demonstrate that, in our investigation, the NARX model outperformed the MLP model. The RMSE metric computes the square root of the average squared discrepancies between expected and actual values, giving a clear indication of prediction accuracy. Lower RMSE values indicate more accuracy. Our results demonstrate that the NARX model had a considerably lower RMSE than the MLP model, indicating a better capacity to estimate wind speed in Dakhla City.

Table 3. Statistical discrepancies generated by the MLP and NARX models

Model	RMSE
Perceptron multicouche	7.67990693
NARX-type RNN	1.028992401

By comparing our results with previous studies [15], [29], [30], we find that the NARX model demonstrates greater efficiency and superior predictive performance compared to the MLP model. This holds true even when the models are applied to different cities and a diverse range of meteorological data, indicating the robustness and generalizability of the NARX model across various scenarios.

4. CONCLUSION

Wind speed predictions in the Dakhla region were conducted employing two ANNs: MLP and RNN. Both networks shared a similar architecture with four input variables: pressure (t-1), temperature (t-1), humidity (t-1), and wind speed (t-1). Additionally, each network included a hidden layer comprising 25 neurons and an activation function, with wind speed at time (t) serving as the decisive factor in the output layer. The NARX model trained using SCG exhibited strong performance, yielding an R-value of 0.99998, whereas the LM Backpropagation method performed less satisfactorily with an R value of 0.51539. This comparison highlights the superior ability of the NARX model over MLPs in effectively addressing nonlinear and complex scenarios. For future research, it would be valuable to explore alternative neural network models, such as long short-term memory (LSTM) networks or gated recurrent units (GRU), to evaluate if they can further enhance prediction accuracy in similar nonlinear conditions. Additionally, incorporating a wider range of exogenous variables, such as solar radiation or seasonal effects, could potentially improve the model's robustness in handling fluctuating environmental facto.

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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Sara Fennane		✓				✓		✓		✓	✓			
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Ibtissam El Moury					✓		✓			✓				✓
Adil Echchelh	✓	✓		✓					✓			✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The dataset underlying this study's findings is publicly accessible in https://www.infoclimat.fr/observations-meteo/temps-reel/dakhla/60034.html. This dataset includes all relevant meteorological parameters used for model training and validation, such as wind speed, temperature, atmospheric pressure, and humidity, collected over the period of 2018–2020 in Dakhla City. The data has been pre-processed and structured to ensure compatibility with MATLAB for neural network training. Researchers can access and utilize the dataset for further studies on wind speed prediction and renewable energy applications.

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